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Towards an Abnormal Bridge Location Identification Method Based on Novelty Detection Technique

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Abstract. The bridge structure abnormality recognition is one of the key steps of its health assessment. Using novelty detection technique based on BP neural network, the method to identify and locate abnormal bridge status was presented. It uses non-training-data in the original sample data to generate novelty indicator and determines threshold. If the difference between detection status indicator and normal value is larger than the threshold, the structure status is determined changed. The method adapts stepwise partition identification method. The method firstly determines damage position within a small range and then analyzes sensor data in detail, so as to locate specific position. The measured data on T beam model verifies the method can accurately carry out status identification and locate cracking position under cracking load conditions.

1 Introduction

Bridge health assessment is an effective method to assess health indicators as structure reliability and durability from processing data obtained from operational structure. The system can monitor operation of bridge scientifically, accurately and timely with information process and data fusion methods, so that the remaining life of key components can be estimated and its health can be objectively and quantitatively evaluated, which is the core of bridge monitoring system.

In order to ensure safe operation and provide technique basis for bridge design, load limit or demolition and reconstruction, it is necessary to carry out capacity test [1] and the fatigue test [2]. However, the existing assessment methods on bridge status abnormality diagnosis and health evaluation mostly rely on specific structure model, specific incentive and single evaluation indicator. Meanwhile, the researches on fatigue life of key components mostly use vehicle load simulating and fatigue stress spectrum estimating methods. In the actual bridge operation, the constantly changing bridge structure parameters lead to difficulty of establishing bridge model. It is difficult to achieve ideal result of abnormal diagnosis, endurance determination and health assessment because of unknown environmental load excitation. In the T beam cracking test, the determination of model crack is always made after comprehensive analysis of data obtained from test [3-4], while the judgment on cracking location commonly uses manual inspection method. Limited by test conditions, complicated sensor node distribution and small crack, it is difficult to determine and locate model crack with eye in the test. It is of practical importance to apply novelty detection technique based on BP neural network to T beam cracking test. The paper is organized as follows: Section 2 presents novelty detection technique based on BP network; Section 3 applies the proposed detection method to T beam cracking test; Section 4 concludes our work.

2 Novelty detection technique based on BP neural network

2.1 Novelty detection technique

The novelty detection is to identify new modes with obvious difference to existing known modes and to extract new, abnormal or unfamiliar features from input data [5]. The novelty detection techniques are mostly implemented with neural network. Using actually measured data under health status, establish mode of structural health status. If the new structural mode has significant difference compared with established mode, the structure is diagnosed as abnormal and deviated from health status. As the neural network has predominant advantages in the pattern recognition filed, the novelty detection can be achieved with neural network as shown in Fig. 1.

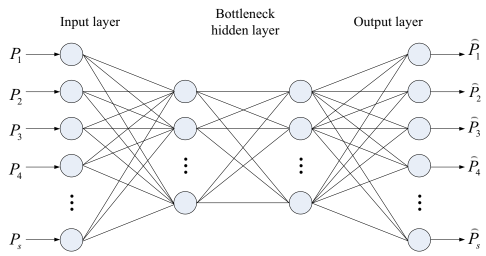

Figure 1. Neural network structure for novelty detection.

As seen from Fig. 1, the network is designed as a multi-layer network with bottleneck hidden layer. The number of input layer is equal to that of output layer. The unit number of bottleneck hidden layer is the smallest to force network learning dominant features of the input vector. The network can be completed with feed-forward BP neural network.

In case of network training, the actual measurement data under health status in the normal operation acts as the input vector and output target. With training, the neural network learns domain feature of input vector to establish mode under healthy structure status. In case of abnormal structure, as the structure mode has changed, the output vector will significantly deviate from input vector, thus status damage identification is achieved.

As the bridge model is complicated and prone to change, the general status identification result completely depends on model establishment. The novelty detection technique can effectively identify damage. The method only needs a certain amount of measure data but not completely depends on numerical model. It can also timely determine damage status to reduce alarm missing, which is of more practical value.

2.2 Detection indicator and threshold settings

In order to determine whether two modes have changed, it needs an indicator to determine the difference between input vector and output vector of BP neural network, which can be represented by a distance function. The paper regards the secondary norm of difference between input vector and output vector as the novelty indication [5].

The measured data under structural normal status is used as input vector for BP neural network training. After network training, the remaining groups of normal data is input into prepared neural network once time as input vector to produce corresponding output vectors. Based on (1) [5], the novelty indicator λ of structural normal status can be arrived.

$$\lambda = \|\hat{P} - P\| = \left(\sum_{i=1}^{N} (\hat{P}_i - P_i)^2 \right)^{\frac{1}{2}} \tag{1}$$

where, P is the input vector of network; $\hat{P}$ is the output vector produced by vector P; N is the dimension of input vector; $\hat{P}_i$ and P_i are the i-the element of vector P and $\hat{P}$ respectively. in order to definitely determine abnormal phenomenon, select threshold as the determination criteria as shown in (2):

$$\delta_\lambda = \bar{\lambda} + 4\sigma_\lambda \tag{2}$$

where, δ_λ is the threshold to determine abnormal data. The $\bar{\lambda}$ and σ_λ are mean and standard difference of multiple normal input vector novelty indicators after neural network training.

The former definition of novelty indicator and threshold all use the indicators in the training phase [6], when the computation of novelty indicator uses input and output vector of training. The flow for novelty indicator and threshold setting is shown in Fig. 2(a). After neural network training, the input vector may infinitely approximate to output vector. In such circumstance, the obtained novelty indicator and threshold may be relatively small, which may lead to false alarm.

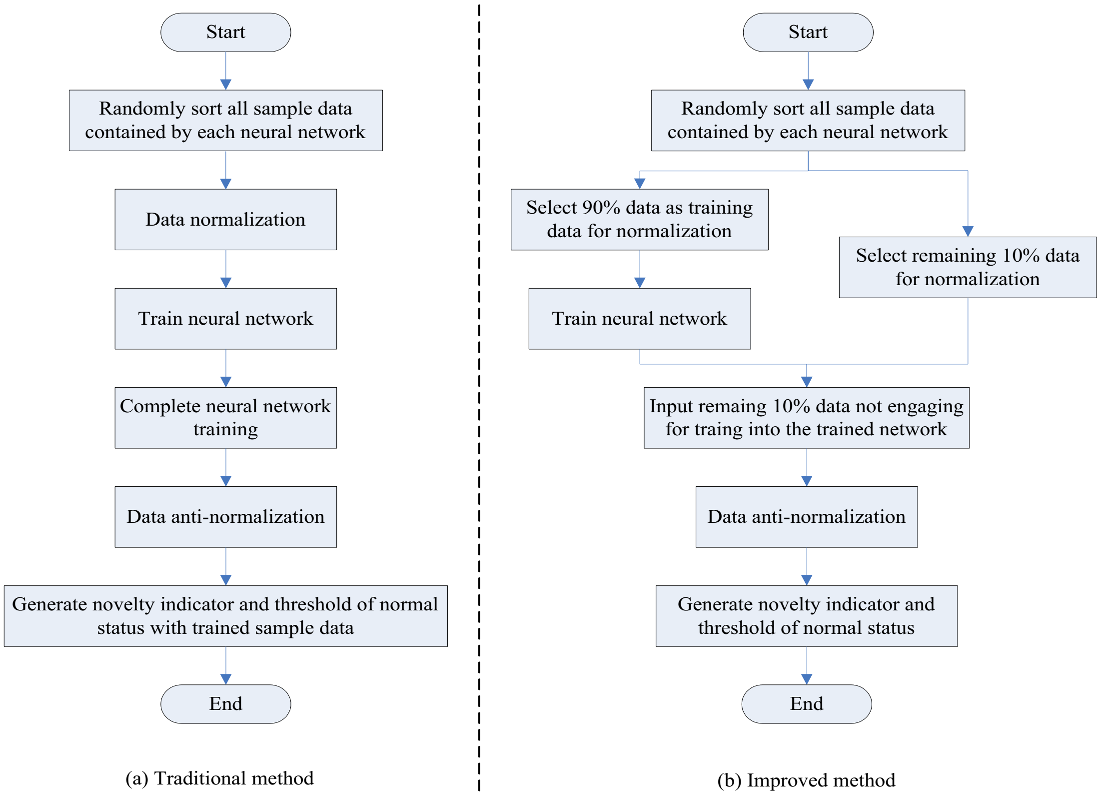

Figure 2. Traditional and improved computation methods for novelty indicator and threshold.

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The paper uses non-training-data in the original sample data to generate novelty indicator as the normal indicator $\overline{\lambda}$ and determines threshold δ_λ. The improved flow is shown in Fig. 2(b). The obtained novelty indicator and threshold can accurately determine structural status.

In the detection phase, the collected measure data is input into trained neural network as the input vector Pt to arrive the output vector $\widehat{P}t$. In accordance with (3), the novelty indicator in the detection phase can be arrived.

$$\lambda t = \left\| \widehat{P}t - Pt \right\| \tag{3}$$

where, λt is the novelty indicator obtained in the abnormal detection phase. Compare the threshold δ_λ to λ_t to determine whether there is abnormal from the difference. If the structural status has changed, the novelty indicator under detection status will be quite different from that under normal structural status. When the difference is larger than determined threshold, we can determine the structural status has changed. In the same way, the degree of status can also be determined in accordance with value of novelty indicator.

3 T beam cracking test based on novelty detection

The paper firstly process collected data in the static load test to generate sample data needed for neural network training. After network training, the model of normal status for T beam based on novelty detection technique can be established to implement abnormal status identification and crack location identification of T beam.

3.1 Test conditions

The test model selected the bridge deck with maximum beam spacing and most unfavorable force for analysis. The load was determined following the equivalent stress principle. Before test, the lateral force of structure was analyzed. The equivalent model test was carried out according to the most unfavorable stress amplitude under designed load. The model selected flange 1:1 scale model. The steel structure is same with design. The model plate used simply supported structure, whose maximum width of flange plate span is 2.535m and plate width is 1m.

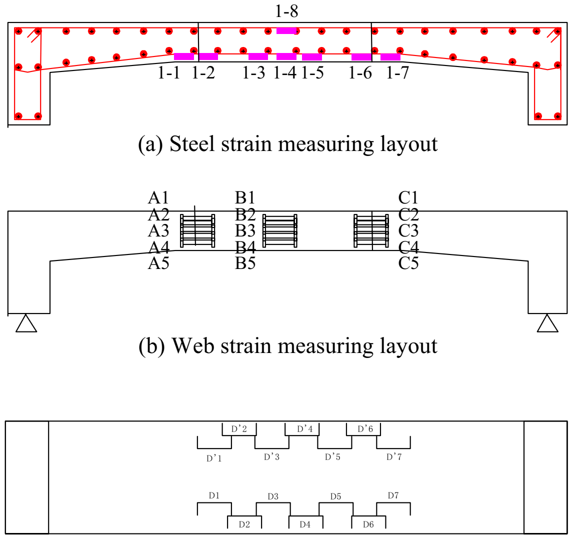
As the model test plate is general reinforced concrete, the cracking moment computation of middle section is as follows:

$$M_{cr} = \gamma f_{tk} W_0 = \frac{2S_0}{W_0} f_{tk} W_0 = 2S_0 f_{tk} \tag{4}$$

where, $S_0 = 1000 \times 100 \times 50 + 10 \times \left(\frac{20}{3.45} - 1 \right) \times \frac{\pi \times 12 \times 12}{4} \times 64 = 5347225mm^3$.

So, $M_{cr} = 2S_0 f_{tk} = 2 \times 5347225 \times 2.65 = 28.34kN \cdot m$ and corresponding concentrated load is 39.0kN.

The crack test includes static load test before cracking, cracking static loading test and post-cracking static load test. In the static load test before cracking, as the theoretical value of cracking load is 39.0kN, we set 5kN as one level till 30kN and then repeat. As the stress load to 30kN not meet the cracking load, when the measurement data is used as training data of neural network. In case of cracking static load test, the stress is loaded till 35kN with 5kN as one level. In order to accurately capture cracking load, the load level was appropriately increase till 70kN. The measuring point layout is shown in Fig. 3.



(a) Steel strain measuring layout

(b) Web strain measuring layout

(c) Floor strain measuring layout

Figure 3. Strain measuring point layout.

According to sensor distribution and finite element analysis model of T beam cracking test, the roles of different sensors are as follows:

Steel strain sensor. The sensor is embedded into T beam structure as shown in Fig. 3(a). It can reflect force status of internal structure in the load test, which is the basis to determine whether the whole structure has changed. The steel strain sensor includes 8 sensors with number from 1-1 to 1-8.

Web strain sensor. The sensors are located on two sides of model web as shown in Fig. 3(b). There are 5 sensors in the wet cross and middle section, total 6 groups, numbered by $A1$-$A5$, $B1$-$B5$, $C1$-$C5$, $A'1-A'5$, $B'1-B'5$, $C'1-C'5$. The aim is to compute height of central axis in the post data analysis. In the paper, each group is processed as a whole to determine status change in the section.

Floor strain sensor. The sensors are located on both outer sides of bridge floor as shown in Fig. 3(c). There are total 14 sensors, divided into 2 groups numbered by D1-D7 and $D'1-D'7$. The target is to capture whether there is crack in the model floor. In the strain loading process, the floor may be crack firstly in theory. Therefore, each group can be regarded as a while for status changing determination. Furthermore, test data of both groups is complementary, increasing accuracy for status determination.

3.2 Generate training sample

Before T beam structure crack test, it needs to carry out static load test before cracking. As the structural status does not change in the test, the test data before cracking can be used as training data for neural network. Under such circumstance, the training data model is neural network model not in cracking structure.

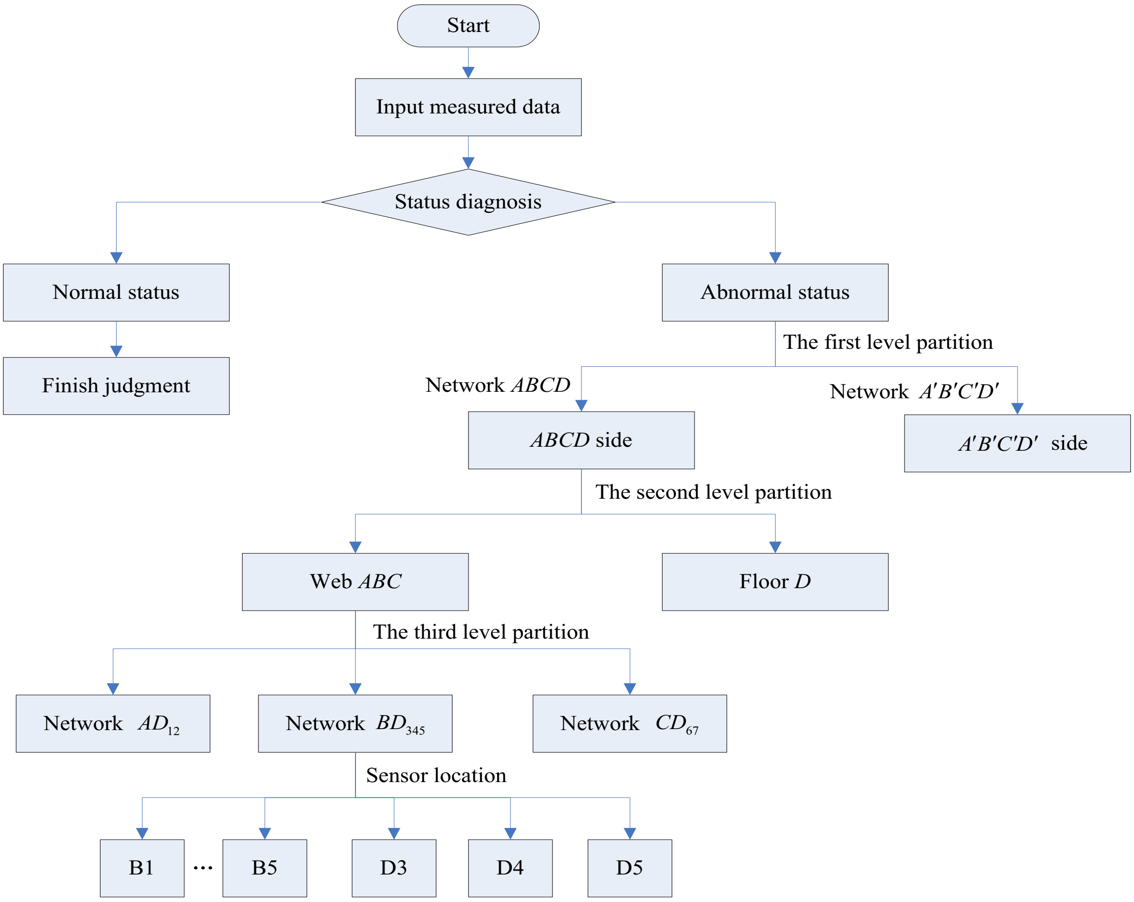


Figure 4. Crack identification and location flow.

As the problems of load process and test method, the sample number is limited. The original 30 groups test data is used as training sample for neural network. In accordance with training flow as shown in Fig. 2(b), the mean of novelty indicator can be arrived as $\bar{\lambda}=49.9$, which is too large. We can modify this structural finite element model based on measured data to obtain more sample data so that the computation result is close to actual measure data from sensors.

Perform validity verification on neural network model trained by increased data with finite element model, taking 1-1 to 1-8 steel strain sensor as example for validation.

Firstly, use 110 groups of sample data, including 60 groups of uncrack steel strain data within 0-30kN simulated by finite element model and original 50 groups of data, as the training sample input into neural network. Input measured data into neural network produced by data from finite element model to obtain the mean of novelty indicator as:

$$\bar{\lambda}=3.16,\ \lambda_{\max}=5.59,\ \sigma_{\lambda}=2.4.$$

The threshold can be computed with (2) that $\delta_{\lambda}=12.7$. The result shows that the neural network model with expanded training sample has lower error and novelty indicator. It indicates that increasing sample amount in the manner of finite element model can also ensure correctness of the network model.

Secondly, in order to verify whether the neural network can identify abnormal structure, verify the steel strain data 0-30*kN* after cracking. The mean of novelty indicator is $\lambda t=104.3$, which is much larger than that in uncrack status. It indicates that the neural network model can identify abnormal changes of the model.

Based on above verification, the cracking load of structure in theory is 40*kN*, so 80 groups of data of each sensor at load 0-40*kN* can be formed as the neural network training sample at normal status. The sample amount can be expanded using the method, thus increasing accuracy of neural network training.

3.3 Neural network level division

As the overall strain network model to measure structural health status, the data of 52 sensors within 0-40*kN* engages in training as a whole. The network structure is designed as 52-40-40-52 four-level feedforward BP network. The transfer functions of second and third layer select tan-sig function. The transfer function between first level and second level, third level and fourth level uses purelin function [7].

Along the loading process, input load data into trained network 1 to perform crack location identification in case of crack alarm. Combining with actual situation of T beam structure, the location identification uses three-level identification manner [7-9].

The first level partition is to determine the sensor side where crack located. The 22 strain values of sensors at $ABCD$ and $A'B'C'D'$ sides are used as input vector for neural network training to arrive at two trained networks, namely network $ABCD$ and network $A'B'C'D'$. Based on these networks, the sensor side where crack located can be identified.

The second level partition aims at identify section of cracks. The structure is divided into 4 cross-sections, forming 4 groups neural networks with 15 and 7 sensor data, namely network web ABC, network web $A'B'C'$, network floor D and network floor D'.

The third level partition constitutes the section with 5 sensors at the web and sensors at the adjacent floor. The structure totally contains 6 sections to form 6 groups of neural networks, namely network AD_{12}, network BD_{345}, network CD_{67}, network $A'D'_{12}$, network $B'D'_{345}$ and network $C'D'_{67}$.

Based on above partition of network model, we can obtain 12 trained neural networks and corresponding novelty indicator and threshold under normal status. After the crack section was located by neural network, the sensor variable value within this section is analyzed to determine specific location. The training flow of ach BP neural network is shown in Fig. 2(b).

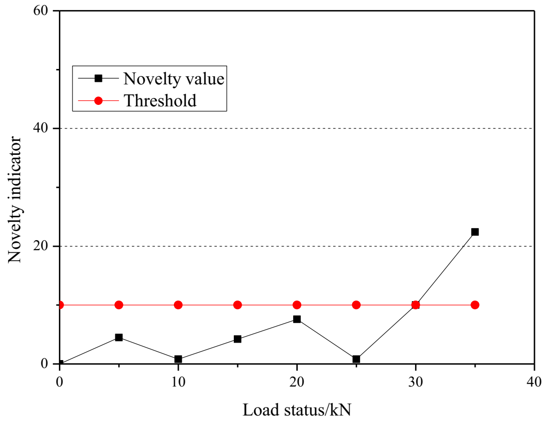


Figure 5. Crack load novelty indicator.

3.4 Crack location identification

The T beam status assessment can be divided into two phases of status identification and location identification. Firstly, the measurement data loaded by level is analyzed to input into trained status identification network, so as to arrive at status identification novelty indicator in the detection phase. If the indicator is normal, the identification ends. In case of abnormal situation, perform abnormal location identification. In the abnormal location identification phase, carry on level-by-level identification with former trained 12 networks to determine abnormal section. Finally, make comprehensive decision in accordance with sensor change rate within the section. The diagnosis flow is shown in Fig. 4.

3.5 Result analysis

When the crack loads 0-40kN, input data of 5kN, 10kN, 15kN, 20kN, 25kN, 30kN, 35kN, 37kN, 39kN and 40kN into network for determination respectively based on load status of each level. The obtained novelty indicator and threshold is shown in Fig. 5. As seen from the figure, the structure changes after loaded to 35kN determined from BP neural network, which is consistent with actual situation.

If the structure has changed, three-level partition manner is used to locate abnormal section. It is found that the novelty of network $ABCD$ and network $A'B'C'D'$ larger than threshold begin from 5kN. That is to say, two sections on side $ABCD$ and side $A'B'C'D'$ have abnormal phenomenon. In case of the second partition identification, the novelty indicator is larger than threshold. It is proven that there are abnormal crack in the web and floor sections, which is identified in the third partition. Part of network novelty indicators in the third partition is shown in Fig. 6 and Fig. 7.

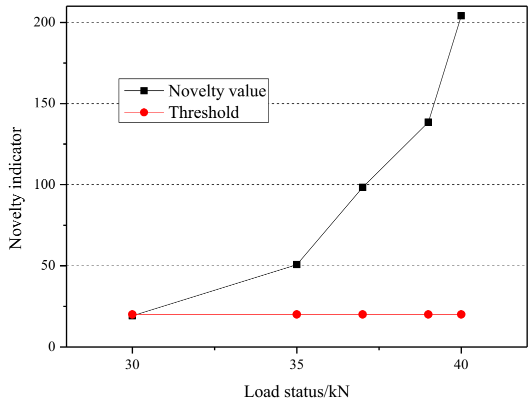


Figure 6. Novelty indicator of network BD_{345}.

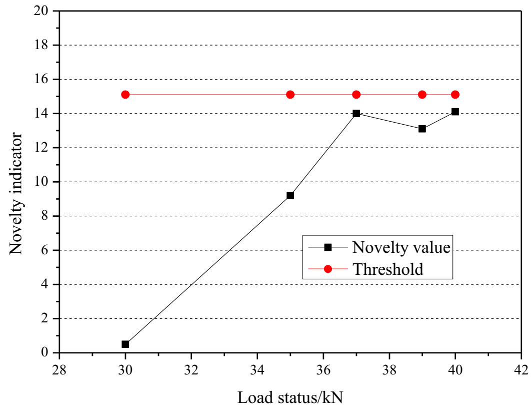


Figure 7. Novelty indicator of network AD_{12}.

We can know from the final section identification that there are abnormal data in the network BD_{345} and network $B'D'_{345}$. Furthermore, the specific position can be located by sensor change rate within the section. Table 1 shows the change rate φ of network BD_{345}.

Table 1. Sensor load change rate φ within BD_{345}.

	B1	B2	B3	B4	B5	D3	D4	D5
30	-2.88	-3.4	0.54	1.1	2.92	3.26	1.9	4.16
35	-3.3	-3.1	-0.22	2.28	4.36	3.58	1.08	5.32
37	-4.6	-0.7	-1.4	3.65	19.2	-0.5	-2.45	25
39	-7.2	-0.25	0.85	11.15	31.5	6.05	-8.05	39.25
40	-1.5	-3.3	10.5	18.7	44.1	5.5	-15.1	53.7

As seen from Table 1, the strain sensor change rate is relatively little compared to $30kN$ in case of $35kN$. It means the manner using single sensor may not determine whether the whole structure has changed. The method can reduce missing alarm to diagnose abnormal structure. Along with load increasing and changing rate, it can determine that the possibility of crack at sensor B5, D4 and D5 is large. Finally, the determine result proves that the measurement values at B5, D4, D5, $B'4$, $B'5$, $D'3$, $D'4$, $D'5$ are abnormal. The determination result is same as that of manual inspection, which proves the validity of the crack identification and location method in the T beam static load test.

4 Conclusion

It is very important of bridge structure health monitoring and damage detection to timely locate structural damage and assess status. The paper discussed method to identify abnormal status of bridge structure and location crack with novelty detection technique based on BP neural network. In order to verify the feasibility of the method in abnormal stratus and location identification, the method was applied in T beam cracking location. In the near future, the data model should be studied so that the method can be applied to overall bridge abnormal status identification more conveniently.

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